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# Predicting Uncompensable Heat Stress with Embedded, Wearable Sensors

John Kemp, Elena Gaura, James Brusey

**Abstract**—The use of heavy protective clothing (such as by EOD operatives) brings problems related to the build-up of heat within the clothing, potentially endangering the health of the wearer and their activities. This paper presents a method of autonomously predicting the onset of thermally dangerous conditions such as Uncompensable Heat Stress in EOD operatives. The method is based on a Dynamic Bayesian Network, trained using Gaussian Kernel Density Estimators based on experimental data. An accuracy of 88.5% was achieved on unseen data when predicting the occurrence of heat stress up to two minutes in the future. The method is intended to be generally applicable to wearers of protective clothing in thermally challenging environments.

## I. INTRODUCTION AND CASE STUDY: MONITORING OPERATIVES DURING EOD MISSIONS

This paper presents a method of autonomously predicting the onset of Uncompensable Heat Stress (UHS) in people wearing heavy protective clothing. Specifically, the case study focused on is that of Explosive Ordnance Disposal (EOD) operatives during missions. EOD missions provide armour designers, disposal operatives, and mission controllers with a number of challenges due to the extreme conditions and strain generated by wearing the armour and by the EOD scenarios encountered. A typical manned EOD mission will involve a human operative being required to walk at least 100 metres to the site of the explosive device while wearing a protective suit (as shown in Figure 1). A full suit consists of a jacket and trousers, along with several under-layers, additional armour plates and inserts, and a helmet, typically weighing around 40 kg. It may be necessary to carry out strenuous or awkward activities such as crawling through passageways, or working under cars. The suit's weight and enclosed nature means that heat build-up becomes a problem, especially when the operative is required to exert himself to complete the mission or the mission takes place in hot climates. This can, in the worst cases, lead to UHS, where the body cannot continue to regulate its temperature effectively [1], [2].

EOD suit manufacturers have attempted to address these problems by installing in-suit cooling systems. One such system is based on blowing cooled air onto the wearer's back and into the helmet [3]. The fan speed is variable to allow the airflow to be adjusted for the wearer's comfort and to extend the life of the batteries that power the fans. Automation of the fan control would allow the operative to focus their attention on the task at hand, while also allowing optimisation for battery life. Such automation would benefit



Fig. 1. Explosive Ordnance Disposal suit.

from a predictive capability, allowing it to provide cooling *prior* to heat stress conditions being encountered.

A Body Sensor Network (BSN)-based instrument has previously been developed [4] that senses physiological parameters of the suit wearer, provides automated cooling actuation, and relays health information, dangerous health condition alerts, and sensed data to a remotely stationed mission observer. A core component in meeting the application requirements is a predictor for the onset of UHS. This enables: 1) automated actuation of the in-suit cooling system to attempt to counteract the condition, 2) feedback to the suit wearer so that they may make an informed decision as to their health and the progress of the mission, and 3) feedback to a remote observer to allow higher-level strategic decisions and (in the worst case) indicate the need for medical aid for the operative. While danger to the operative can never be completely eliminated, these benefits aid in preventing health problems related to use of the EOD suit. While the stated application motivated this work, a range of other applications could benefit from a system of this type.

The paper is structured as follows: Section 2 provides a brief overview of related work in the literature, Section 3 describes the prediction model developed, Section 4 presents example results based on experimental data, and Section 5 concludes the paper.

## II. LITERATURE

### A. Uncompensable Heat Stress

A potentially dangerous phenomenon in thermally harsh environments is that of UHS, which occurs when the cooling required to maintain a steady thermal state is greater than the cooling capability of the environment [5]. Jang *et al.* [6] investigated heat stress in relation to soldiers in hot climates, while Thake *et al.* [7] and Cheung *et al.* [5] investigated the onset of UHS specifically in relation to wearers of EOD

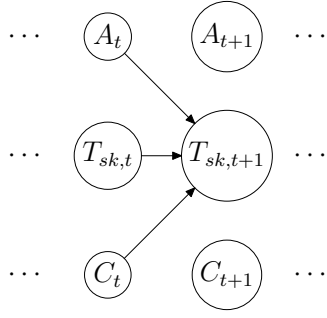


Fig. 2. A simple DBN model of the effect of cooling  $C_t$ , activity  $A_t$  and mean skin temperature  $T_{sk,t}$  on future mean skin temperature  $T_{sk,t+1}$ .

suits. A related concept is that of heat storage, which is caused by a lack of sufficient cooling capability. This is generally modelled using heat balance equations [8] based on the heat production within the body, heat loss via the skin, and heat loss via respiration. Heat storage occurs when the heat produced is greater than the heat lost, and the condition of UHS implies heat storage occurring in a situation where the body is unable to significantly reduce it. The result of heat storage is that the core body temperature will rise. In the case of UHS this will continue beyond safe levels, endangering the health of the operative as described in the next section. Thus, prediction of the onset of UHS will rely on the monitoring and prediction of the evolution of core body temperature.

#### B. Core temperature measurement and estimation

Even small deviations in core temperature have the potential to cause impairment of coordination and psychological function. In general, a change of up to 2 °C away from the normal core temperature will cause extreme discomfort, and a change of 4 °C or more will require medical attention. There are two main approaches commonly used to measure a subject's core temperature, neither of which is suitable in the application here:

- Telemetry pills, such as the HQ Inc. CorTemp pill [9]. However, ingestion of fluids is advisable for rehydration when wearing an EOD suit and this can cause large variations in the pill's readings [10].
- Aural or rectal probe. In addition to the distraction caused by these types of sensor, aural probes are difficult to securely attach when a helmet is worn, and rectal probes require the subject to remove clothing during the setup procedure (which does not typically occur during preparation for an EOD mission).

Given that core temperature is not practical to be measured in EOD missions, an alternative is to use skin temperature (a relatively accessible parameter) as the basis of core temperature estimation or as a direct measurement proxy [11], [12]. There are some constraints in the use of skin temperature as it depends on the ambient temperature, local air circulation, and blood circulation. Within the EOD suit, the restricted air circulation is likely to reduce transients in skin temperature, allowing reliable estimation.

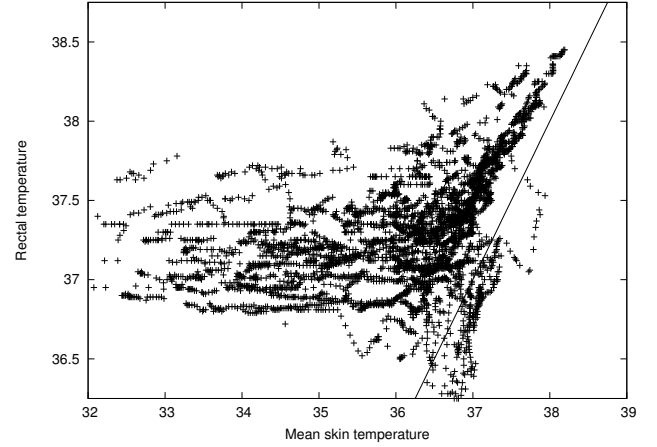


Fig. 3. Subject mean skin temperature and rectal temperature. The line indicates equal mean skin and rectal temperatures.

### III. HEAT STRESS PREDICTION ALGORITHM

The heat stress prediction algorithm is based around a Dynamic Bayesian Network (DBN) incorporating the subject's current activity, the cooling applied to the subject, and the subject's mean skin temperature as a proxy for core temperature. These factors are key for the onset of heat stress in the EOD case study.

At the core of the predictor is a probabilistic model based on the DBN shown in Figure 2. In this model, it is assumed that activity  $A_t$ , cooling level  $C_t$ , and mean skin temperature  $T_{sk,t}$  are sufficient to allow prediction of future mean skin temperature and that the tuple  $\langle A, C, T_{sk} \rangle$  has the Markov property (knowing the past history would not improve the prediction). This is clearly a simplified model of the thermal interactions internally and externally to the human body. This simplification is necessary here: 1) to allow accurate derivation of model parameters from a limited number of trials, and, 2) to ensure that prediction can be performed on a computationally constrained platform in real-time as required by the application.

There are two parameters that must be determined prior to training and using the predictor:

- 1) A unit of time defining how far into the future the prediction is needed. In this work, *two minute* prediction is used and so  $t+1$  is taken to mean "the current time plus two minutes."
- 2) The mean skin temperature to be used as a "danger" threshold. Here, a relatively low threshold value of  $T_d = 36.5$  °C is used due to the safety limits of the trials used to form the model.

It has been observed in the trial conditions considered here that the core temperature starts to rise proportionally with mean skin temperature once the latter has reached 36.5 °C (demonstrated in Figure 3). Hyperthermia is defined to start with core temperatures above 37.5 °C, roughly corresponding to 37 °C mean skin temperature according to Figure 3.

The model allows us to predict the probability of heat stress

TABLE I

PROBABILITY OF EXCEEDING THE THRESHOLD  $T_d = 36.5$  °C WITHIN 2 MINUTES GIVEN ACTIVITY AND COOLING TYPE FOR  $T_{sk,t} = 36$  °C (TOP) AND  $T_{sk,t} = 36.25$  °C (BOTTOM).

	Walking	Kneeling	Crawling	Arm ex.	Sitting	Overall
NC	0.63	0.26	0.40	0.93	0.87	0.83
CC	0.70	0.74	0.68	0.65	0.78	0.73
HC	0.86	0.79	0.80	0.72	0.82	0.81

	Walking	Kneeling	Crawling	Arm ex.	Sitting	Overall
NC	0.98	0.86	0.84	0.99	0.97	0.97
CC	0.76	0.86	0.82	0.84	0.90	0.85
HC	0.94	0.92	0.92	0.92	0.97	0.95

by finding the probability of the threshold temperature being reached or exceeded. For brevity,  $d$  (for “danger”) is defined to be the event  $T_{sk,t+1} > T_d$ , and  $\bar{d}$  is its negation. Therefore, the goal is to determine  $P(d|T_{sk,t}, A_t, C_t)$ . Training data gathered from experimental trials using the suit is used to find Probability Density Functions (PDFs)  $P(T_{sk,t}|d, A_t, C_t)$  and  $P(T_{sk,t}|\bar{d}, A_t, C_t)$  and then Bayes’ rule is applied to find  $P(d|T_{sk,t}, A_t, C_t)$  via

$$P(d|T_{sk,t}, A_t, C_t) = \alpha P(T_{sk,t}|d, A_t, C_t) P(d, A_t, C_t)$$

where  $\alpha$  is a normalising constant such that the conditional probability of  $d$  and  $\bar{d}$  sum to 1. Specifically,

$$\alpha = 1 / (P(d|T_{sk,t}, A_t, C_t) + P(\bar{d}|T_{sk,t}, A_t, C_t))$$

To form a good fit for the available data, each PDF is approximated using a Gaussian Kernel Density Estimator.

#### IV. EXAMPLE DATA AND RESULTS

Data from a total of 26 trials was used [13]. Twelve subjects underwent a mission-like protocol while wearing the EOD suit at 40 °C ambient temperature and three different in-suit cooling variations—no cooling (NC), chest cooling (CC), and head cooling (HC). The trials consisted of four identical back-to-back cycles of: walking on a treadmill (3 mins), kneeling while moving weights (2 mins), crawling (2 mins), postural testing (2.5 mins), arm exercise while standing (3 mins), and cognitive tests while sitting (6 mins). The first cycle performed in each trial was excluded from the data used in the analysis here due to non-representative rapid changes in skin temperature during this cycle.

Due to the issue of safety in experimentation, there was not sufficient data available to support calculation using this algorithm with skin temperatures approaching and exceeding normal core temperature. This method is, however, expected to function correctly for any given value of  $T_d$  when sufficient data is available. Therefore a lower value of 36.5 °C was chosen for this evaluation.

Figure 4 shows mean skin temperature against  $P(d)$  for each of the three cooling variations, while Table I shows  $P(d)$  for mean skin temperatures of 36 °C and 36.25 °C. Table I reveals some interesting characteristics of the model. First, the highest probability of reaching the “danger” threshold within two minutes for subjects, at 36 °C, occurs for

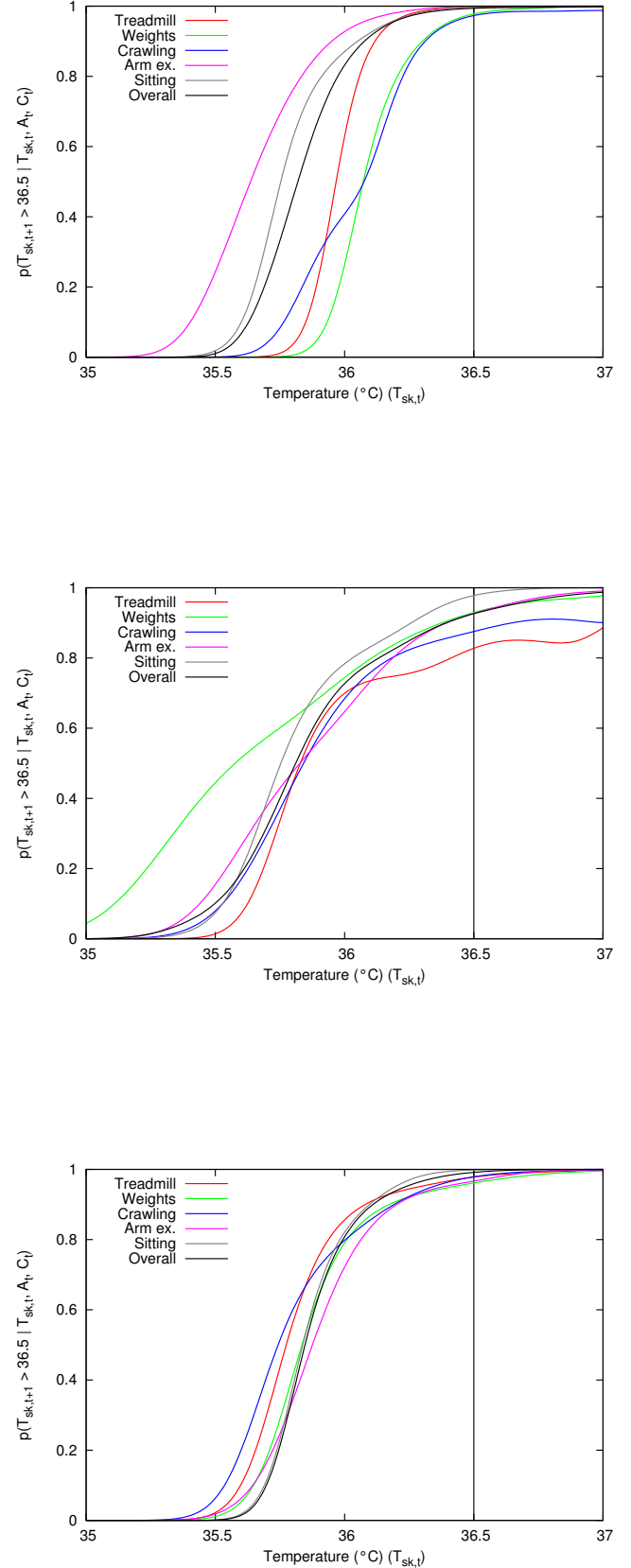


Fig. 4. Mean skin temperature against  $P(T_{sk,u} \geq T_d | T_{sk,t})$  for three cooling variations with  $T_d = 36.5$  °C. Top: no cooling. Centre: chest cooling. Bottom: head cooling. Curves are shown for individual activities and for an aggregate (as would be used if activity information is not known).

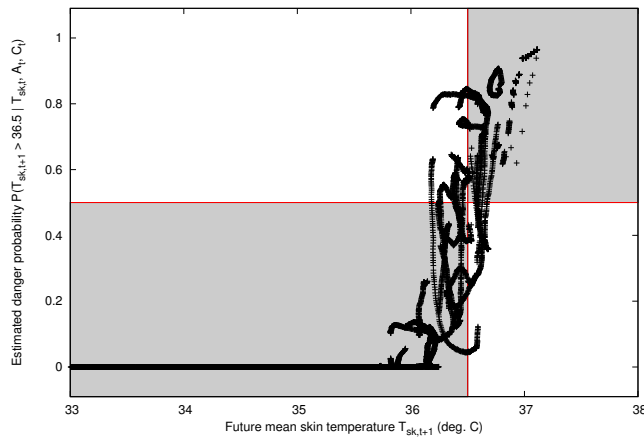


Fig. 5. Performance of the Bayesian model on test data with the “future” mean skin temperature horizontally (i.e. the temperature after 2 minutes). The shaded regions are counted as accurate—probability below 0.5 for future temperatures below 36.5 °C and above 0.5 for temperatures above.

those performing arm exercises or sitting without cooling. Second, the probability increases for all subjects when they reach 36.25 °C. Third, the lowest probability of danger occurs for those at 36 °C performing kneeling or crawling activities without cooling. This last item appears counter-intuitive: these activities are strenuous and the lack of cooling would seem to be a disadvantage to these subjects. A possible explanation is that the cooling system is lowering the apparent body temperature as measured by mean skin temperature and thus the effective body temperature (due to heat stored in fat and muscles) for cooled subjects is actually much higher than 36 °C. This observation may indicate that the Markov assumption does not hold. In other words, a better prediction of future temperature might be possible if more of the temperature history were known. A possible solution to this is to incorporate into the model state some estimate for the “stored heat”.

Applying the trained model to a test data set yields the graph in Figure 5. For evaluation purposes, the output from the predictor is classed as correct if the generated probability is over 0.5 when the future mean skin temperature is over 36.5 °C, and vice versa (the regions shown shaded grey in Figure 5). Given this criteria, the overall accuracy of the predictor was 88.5% for the test data used. This demonstrates that the model is a usable predictor of whether the danger threshold will be exceeded, since most instances where the future temperature was below 36.5 °C yield a probability close to zero while most instances where the future temperature was above the threshold yield a high probability according to the trained model.

## V. CONCLUSIONS

A predictor has been developed and implemented to give early warning of UHS onset for wearers of heavy protective clothing. It takes into account the current activity and applied cooling. The predictor has been trained and tested using experimental skin temperature data gathered from subjects

performing mission-like protocols while wearing an EOD suit and gave an accuracy of 88.5% when predicting mean skin temperature exceeding a threshold of 36.5 °C within the next two minutes.

The model as it exists currently may not satisfy the Markov property. There are two possible avenues that could be explored in future work to resolve this:

- 1) Apply a modelling approach that does not require the Markov property (such as Gaussian Process Regression), or,
- 2) Incorporate into the model an estimate of the body’s stored heat.

Nonetheless, the Bayesian approach appears to be a promising one and is expected to form a solid basis for ensuring mission safety and supporting an automatic feedback control system.

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